SCIENCE
PASSION
TECHNOLOGY

Data Integration and Analysis 05 Entity Linking and Deduplication

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Last update: Nov 05, 2021

ISDS

Announcements/Org

- **#1 Video Recording**
  - Link in **TUbe** & **TeachCenter** (lectures will be public)
  - Optional attendance (independent of COVID)
  - **Hybrid**, in-person but video-recorded lectures
    - **HS i5** + Webex: https://tugraz.webex.com/meet/m.boehm
- **#2 COVID-19 Precautions** (HS i5)
  - Room capacity: 24/48 (green/**yellow**), 12/48 (orange/red)
- **#3 Exercises / Programming Projects**
  - Project Selection by **Nov 05, 11.59pm**
  - WS 20/21 DIA projects still valid
- **#4 Exam Date**
  - **Feb 04, 3pm-5pm** in HS i13 (76 seats)

max

24/116

41/116

Announcements/Org

- **#4 Exercise Help**
  - How to even parse/convert the data in a distributed manner?

```
#index 1                P1
#* Paper Title 1
#@ Author1, Author2
#t 2021
#% ref1
#% ref2

#index 2
#* Paper Title 2
#@ Author4               P2
#t 2020

#index 3
#* Paper Title 3
#@ Author2, Author3
#t 2021
#% ref5
```

Option 1: Custom TextInputFormat w/ split at empty line or '#index' → one record per paper

Option 2: Default TextInputFormat and grouping via cumulative aggregates

```
lines = sc
  .textfile(“./AMiner-Paper.txt”)
  .zipWithIndex(); //Tuple2<String,Long>
pos = lines
  .filter(r -> r._1().startsWith(“#index”))
  .map(r -> r._2()).collect()
posArray[pos] = 1;                Local
posArray = cumsum(posArray);
b = sc.broadcast(posArray);
papers = lines
  .map(r -> (b[r._2()-1], r._1()))
  .reduceByKey() //shuffling
```

```
1   1
0   1
0   1
0   1
0   1
0   1
0   1
1   2
0   2
0   2
0   2
0   2
1   3
0   3
0   3
0   3
0   3
```

Agenda

- **Motivation and Terminology**
- **Entity Resolution Concepts**
- **Entity Resolution Tools**
- **Example Applications**

Motivation and Terminology

Recap: Corrupted/Inconsistent Data

- **#1 Heterogeneity of Data Sources**
  - Update anomalies on denormalized data / eventual consistency
  - Changes of app/prep over time (US vs us) → inconsistencies
- **#2 Human Error**
  - Errors in semi-manual data collection, laziness (see default values), bias
  - Errors in data labeling (especially if large-scale: crowd workers / users)
- **#3 Measurement/Processing Errors**
  - Unreliable HW/SW and measurement equipment (e.g., batteries)
  - Harsh environments (temperature, movement) → aging

No Global Keys

Uniqueness & duplicates **Contradictions & wrong values** **Missing Values** **Ref. Integrity**

[**Credit:** Felix Naumann]

ID	Name	BDay	Age	Sex	Phone	Zip
3	Smith, Jane	05/06/1975	44	F	999-9999	98120
3	John Smith	38/12/1963	55	M	867-4511	11111
7	Jane Smith	05/06/1975	24	F	567-3211	98120

Zip	City
98120	San Jose
90001	Lost Angeles

Typos

Terminology

[Douglas Burdick, Ronald Fagin, Phokion G. Kolaitis, Lucian Popa, Wang-Chiew Tan: Expressive power of entity-linking frameworks. **J. Comput. Syst. Sci. 2019**]

- **Entity Linking**
  - "***Entity linking*** is the problem of creating links among records representing real-world entities that are related in certain ways."
  - "As an important special case, it includes **entity resolution**, which is the problem of **identifying or linking duplicate entities**
- **Other Terminology**
  - Entity Linking → Entity Linkage, Record Linkage
  - Entity Resolution → Data Deduplication, Entity Matching

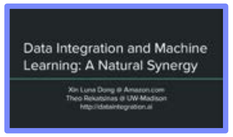
☺

- **Applications**
  - Named entity recognition and disambiguation
  - Archiving, knowledge bases and graphs
  - Recommenders / social networks
  - Financial institutions (persons and legal entities)
  - Travel agencies, transportation, health care

Barack Obama
Barack Hussein Obama II
The US president (2016)

Barack and **Michelle**
are married ….

Entity Resolution Concepts


Data Integration and Machine Learning: A Natural Synergy
Xin Luna Dong @ Amazon.com
Theo Rekatsinas @ UW-Madison
http://dataintegration.ai

[Xin Luna Dong, Theodoros Rekatsinas: Data Integration and Machine Learning: A Natural Synergy. Tutorials, **SIGMOD 2018**, **PVLDB 2018**, **KDD 2019**]

Learning-Based Methods with Human in the Loop for Entity Resolution

[Sairam Gurajada, Lucian Popa, Kun Qian, Prithviraj Sen: Learning-Based Methods with Human in the Loop for Entity Resolution, Tutorial, **CIKM 2019**]

Master project seminar for
Distributed Duplicate Detection
Winter Semester 2016
Supervisor: Felix Naumann
Advisors: Ahmad Samiei · Ahmad.Samiei@hpi.de
John (Ioannis) Koumarelas · Ioannis.Koumarelas@hpi.de

[Felix Naumann, Ahmad Samiei, John Koumarelas: Master project seminar for Distributed Duplicate Detection. Seminar, **HPI WS 2016**]

Problem Formulation

- **Entity Resolution**
  - "Recognizing those records in two files which represent identical persons, objects, or events"
  - Given two data sets A and B
  - Decide for all pairs of records $a_i - b_j$ in A x B if match (**link**), no match (**non-link**), or not enough evidence (**possible-link**)

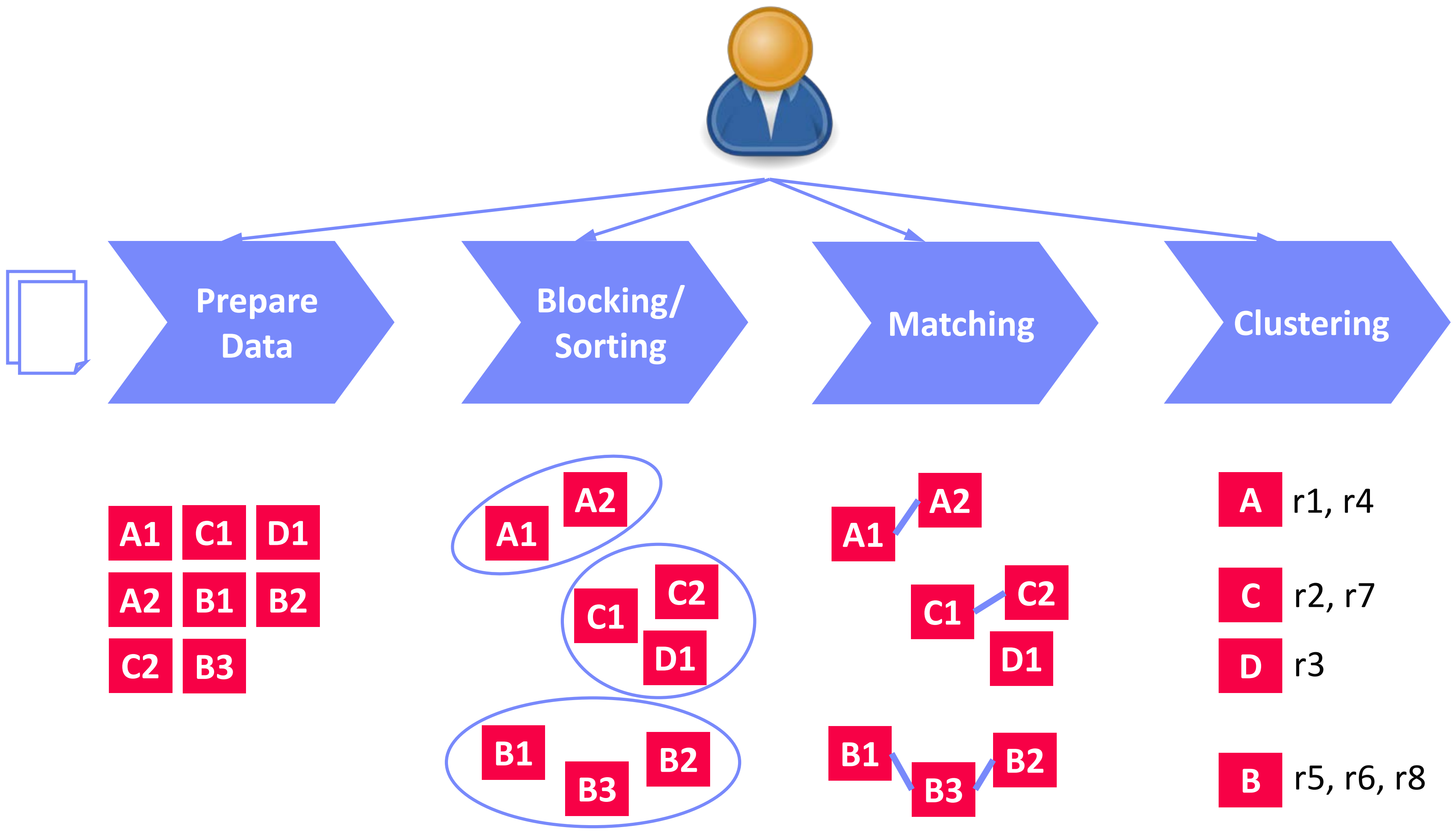
[Ivan Fellegi, Alan Sunter: A Theory for Record Linkage, J. American. Statistical Assoc., pp. 1183-1210, **1969**]

- **Naïve Deduplication**
  - UNION DISTINCT via hash group-by or sort group-by
  - **Problem:** only exact matches

Name	Position	Affiliation	Research
Matthias Boehm	RSM	IBM Research – Almaden	Apache SystemML
Matthias Böhm	Prof	TU Graz	Apache SystemDS

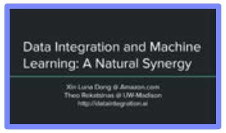
→ **Similarity Measures**
  - Token-based: e.g., Jaccard J(A,B) = (A ∩ B) / (A ∪ B)
  - Edit-based: e.g., Levenshtein lev(A,B) → min(replace, insert, delete)
  - Phonetic similarity (e.g., soundex, metaphone), **Python lib Jellyfish**

Entity Resolution Pipeline



Entity Linking Approaches

[Xin Luna Dong, Theodoros Rekatsinas:
Data Integration and Machine Learning:
A Natural Synergy. **PVLDB 2018**]



Data Integration and Machine Learning: A Natural Synergy

Xin Luna Dong @ Amazon.com
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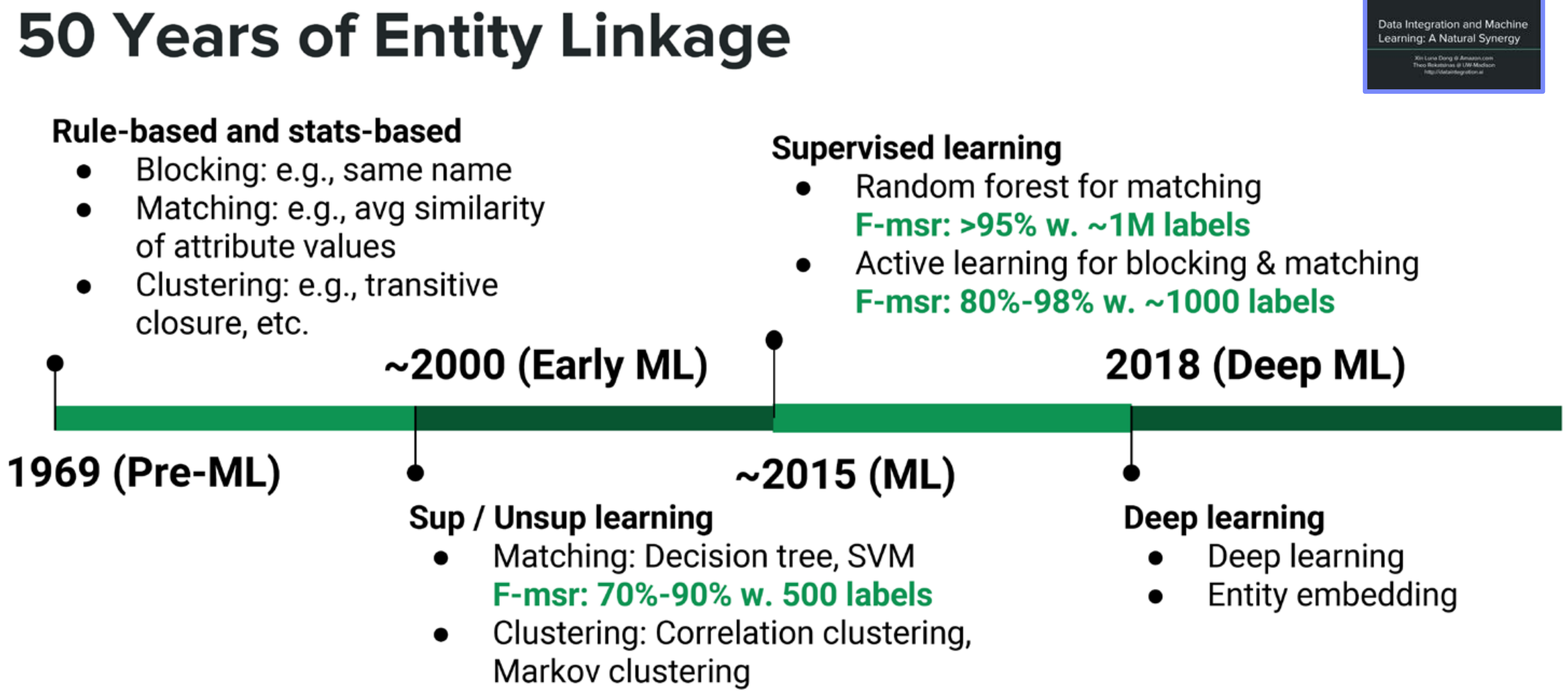


50 Years of Entity Linkage

1969 (Pre-ML)

Rule-based and stats-based
- Blocking: e.g., same name
- Matching: e.g., avg similarity of attribute values
- Clustering: e.g., transitive closure, etc.

~2000 (Early ML)

Sup / Unsup learning
- Matching: Decision tree, SVM
  F-msr: 70%-90% w. 500 labels
- Clustering: Correlation clustering, Markov clustering

~2015 (ML)

Supervised learning
- Random forest for matching
  F-msr: >95% w. ~1M labels
- Active learning for blocking & matching
  F-msr: 80%-98% w. ~1000 labels

2018 (Deep ML)

Deep learning
- Deep learning
- Entity embedding

Step 1: Data Preparation

- **#1 Schema Matching and Mapping**
  - See lecture **04 Schema Matching and Mapping**
  - Create **homogeneous schema** for comparison
  - Split composite attributes

Autonomous, heterogeneous systems

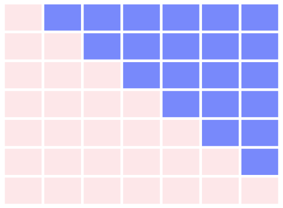
- **#2 Normalization**
  - Removal of special characters and white spaces
  - **Stemming**
  - **Capitalization** (to upper/lower)
  - Remove redundant works, resolve abbreviations

likes/liked/likely/liking
$\rightarrow$ like

- **#3 Data Cleaning**
  - See lecture **06 Data Cleaning and Data Fusion**
  - Correct data corruption and inconsistencies

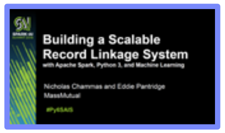
Step 2: Blocking and Sorting

- **#1 Naïve All-Pairs**
  - Brute-force, naïve approach
    → n*(n-1)/2 pairs → **O(n²) complexity**



- **#2 Blocking / Partitioning**
  - Efficiently create small blocks of similar records for pair-wise matching
  - **Basic:** equivalent values on selected attributes (name)
  - **Predicates:** whole field, token field, common integer, same x char start, n-grams
  - **Hybrid:** disjunctions/conjunctions
  - Blocking Keys: → JR01111

John Roberts	20 Main St	Plainville	MA	01111



Building a Scalable Record Linkage System

[Nicholas Chammas, Eddie Pantrige: Building a Scalable Record Linkage System, **Spark+AI Summit 2018**]

  - Learned: Minimal rule set via greedy algorithms

➔ **Significant reduction:** 1M records → 1T pairs
➔ 1K partitions w/ 1K records → 1G pairs (**1000x**)

Step 2: Blocking, cont.

- **#3 Sorted Neighborhood**
  - Define **sorting keys** (similar to blocking keys)
  - Sort records by sorting keys
  - Define **sliding window of size m** (e.g., 100) and compute all-pair **matching within sliding window**
- **#4 Blocking via Word Embeddings and LSH/DL**
  - Compute word/attribute embeddings + tuple embeddings
  - **Locality-Sensitive Hashing (LSH)** for blocking
  - K hash functions h(t) → k-dim hash-code
  - L hash tables, each k hash functions

Distributed Tuple Representation

[Muhammad Ebraheem et al: Distributed Representations of Tuples for Entity Resolution. **PVLDB 2018**]

[Saravanan Thirumuruganathan et al. Deep Learning for Blocking in Entity Matching […]. **PVLDB 2021**]

```
V %*% H          h1=[-1, 1,1], h2=[ 1,1, 1],
                 h3=[-1,-1,1], h4=[-1,1,-1],

v[t1]=[0.45,0.8,0.85]  [1.2,2.1,-0.4,-0.5]     [1,1,-1,-1]     [12]  Hash
                                            →                →
v[t2]=[0.4,0.85,0.75]  [1.2,2.0,-0.5,-0.3]     [1,1,-1,-1]     [12] bucket
```

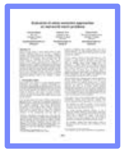
Step 3: Matching

- **#1 Basic Similarity Measures**
  - Pick similarity measure sim(r, r') and thresholds: high θ_h (and low θ_l)
  - Record similarity: avg attribute similarity
  - **Match:** sim(r, r') > θ_h **Non-match:** sim(r, r') < θ_l
    possible match: θ_l < sim(r, r') < θ_h

- **#2 Learned Matchers (Traditional ML)**
  - **Phase 1:** Learned string similarity measures for selected attributes
  - **Phase 2:** Training matching decisions from similarity metrics
  - Selection of samples for labeling (sufficient, suitable, **balanced**)
  - **SVM** and **decision trees**, **logistic regression**, **random forest**, XGBoost

[Mikhail Bilenko, Raymond J. Mooney: Adaptive duplicate detection using learnable string similarity measures. **KDD 2003**]

[Hanna Köpcke, Andreas Thor, Erhard Rahm: Evaluation of entity resolution approaches on real-world match problems. **PVLDB 2010**]



[Xin Luna Dong: Building a Broad Knowledge Graph for Products. **ICDE 2019**]

Step 3: Matching, cont.

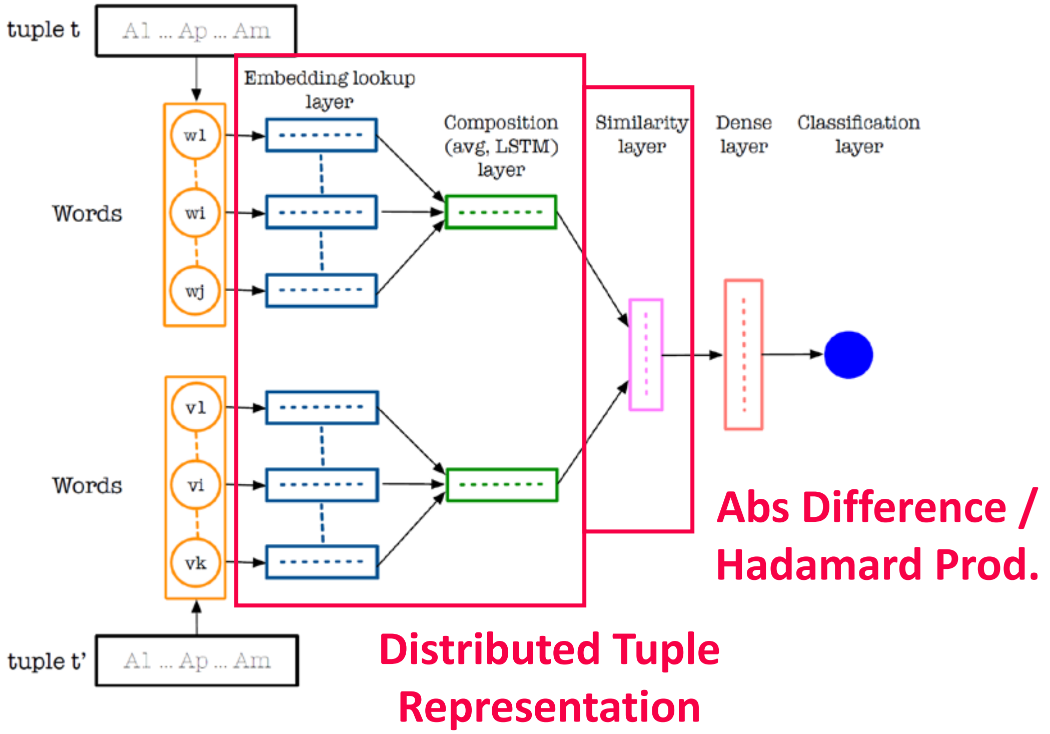
- **Deep Learning for ER**
  - Automatic **representation learning** from text (avoid feature engineering)
  - Leverage pre-trained **word embeddings for semantics** (no syntactic limitations)

- **Example DeepER**

[Muhammad Ebraheem et al: Distributed Representations of Tuples for Entity Resolution. **PVLDB 2018**]

- **Example Magellan**
  - DL for text and dirty data

[Sidharth Mudgal et al: Deep Learning for Entity Matching: A Design Space Exploration. **SIGMOD 2018**]

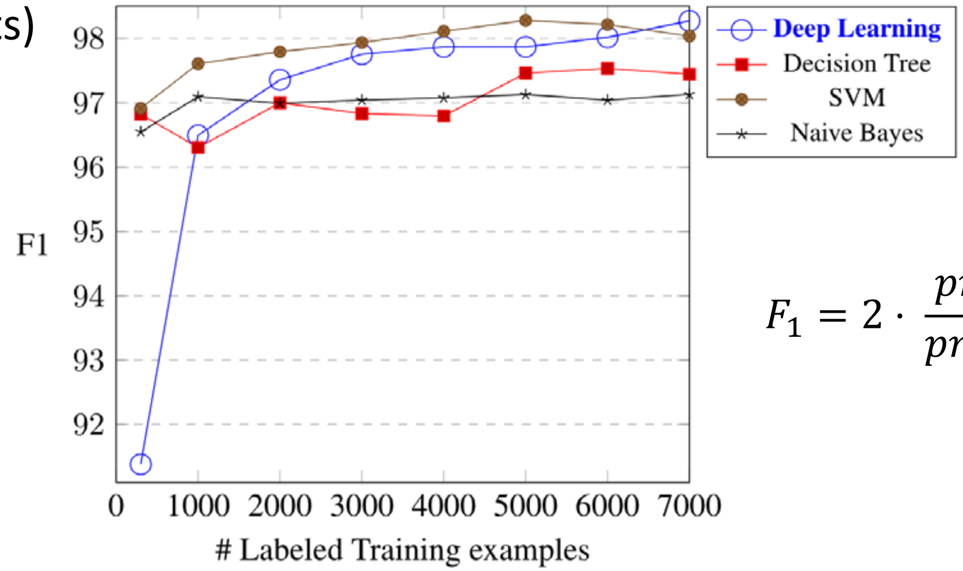


Step 3: Matching, cont.

[Sairam Gurajada, Lucian Popa, Kun Qian, Prithviraj Sen: Learning-Based Methods with Human in the Loop for Entity Resolution, Tutorial, **CIKM 2019**]

- **Labeled Data**
  - Scarce (experts)
  - Class skew

DBLP-ACM



$$F_1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$$

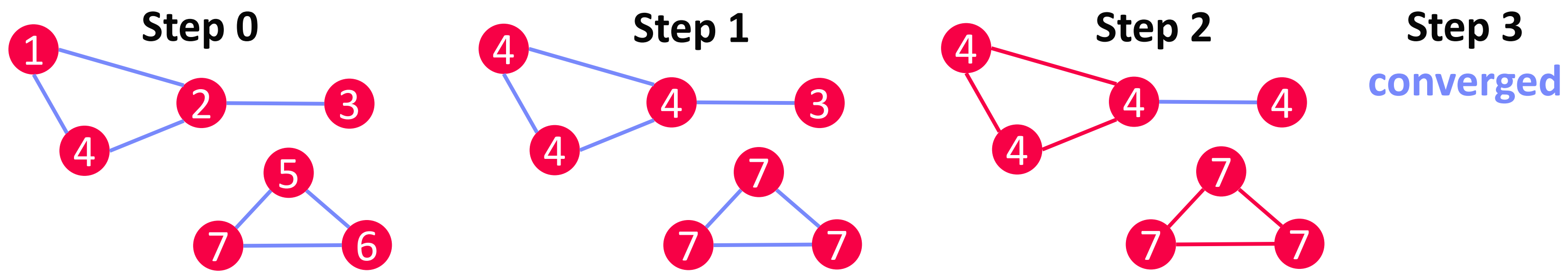
➔ **Transfer Learning**
  - Learn model from high-resource ER scenario (w/ regularization)
  - Fine-tune using low-resource examples

➔ **Active Learning**
  - Select instances for tuning to min labeling

[Jungo Kasai et al: Low-resource Deep Entity Resolution with Transfer and Active Learning. **ACL 2019**]

Step 4: Clustering

- **Recap: Connected Components**
  - Determine connected components of a graph (subgraphs of connected nodes)
  - Propagate max(current, msgs) if != current to neighbors, terminate if no msgs



- **Clustering Approaches**
  - **Basic:** connected components (transitive closure) w/ edges sim > θ_h → Issues: **big clusters** and **dissimilar records**
  - **Correlation clustering:** +/- cuts based on sims → global opt NP-hard
  - **Markov clustering:** stochastic flow simulation via random walks

[Oktie Hassanzadeh, Fei Chiang, Renée J. Miller, Hyun Chul Lee: Framework for Evaluating Clustering Algorithms in Duplicate Detection. **PVLDB 2009**]

Incremental Data Deduplication

[Anja Gruenheid, Xin Luna Dong, Divesh Srivastava: Incremental Record Linkage. **PVLDB 2014**]

- **Goals**
  - Incremental stream of updates
    → previously **computed results obsolete**
  - Same or **similar results** AND **significantly faster** than batch computation

- **Approach**
  - End-to-end incremental record linkage for new and changing records
  - Incremental maintenance of similarity graph and incremental graph clustering
  - Initial graph created by **correlation clustering**
  - Greedy update approach in polynomial time
    - Directly connect components from increment ΔG into Q
    - **Merge** of **pairs of clusters** to obtain better result?
    - **Split** of **cluster into two** to obtain better result?
    - **Move** nodes **between two clusters** to obtain better result?

Entity Resolution Tools

Python Dedupe

https://docs.dedupe.io/en/latest/API-documentation.html
https://dedupeio.github.io/dedupe-examples/docs/csv_example.html

- **Overview**
  - Python library for data deduplication (entity resolution)
  - **By default:** logistic regression matching (and blocking)
- **Example**

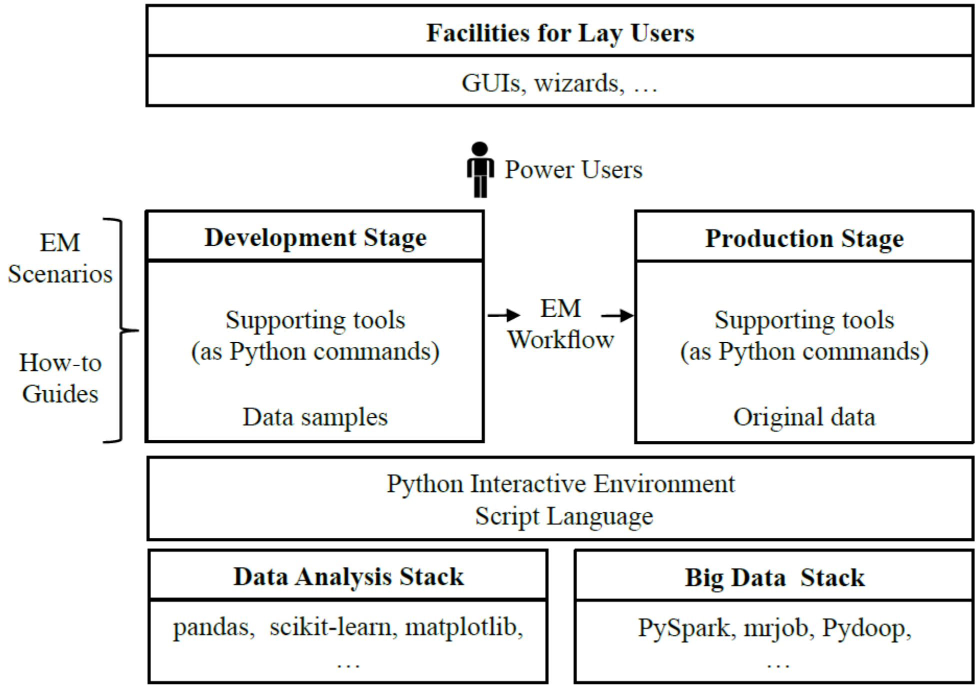
```
fields = [
  {'field':'Site name', 'type':'String'},
  {'field':'Address', 'type':'String'}]
deduper = dedupe.Dedupe(fields)

# sample data and active learning
deduper.sample(data, 15000)
dedupe.consoleLabel(deduper)

# learn blocking rules and pairwise classifier
deduper.train()

# Obtain clusters as lists of (RIDs and confidence)
threshold = deduper.threshold(data, recall_weight=1)
clustered_dupes = deduper.match(data, threshold)
```

```
Do these records refer
 to the same thing?
  (y)es / (n)o /
(u)nsure / (f)inished
```

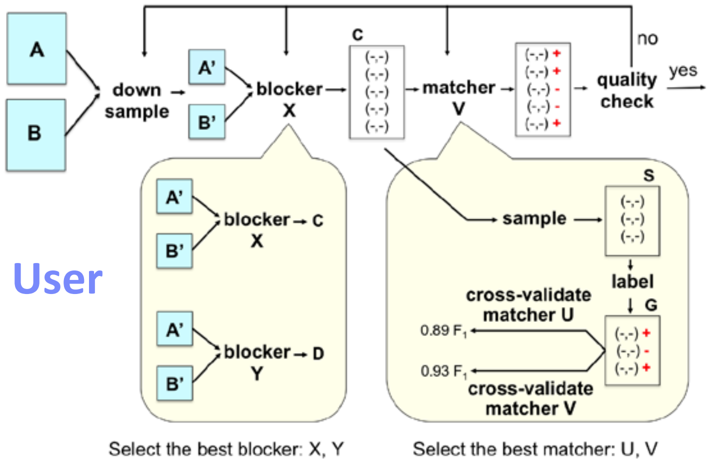
Magellan (UW-Madison)

[Pradap Konda et al.: Magellan: Toward Building Entity Matching Management Systems. **PVLDB 2016**]

- **System Architecture**
  - **How-to guides for users**
  - Tools for individual steps of **entire ER pipeline**
  - Build on top of existing Python/big data stack
  - Scripting environment for power users



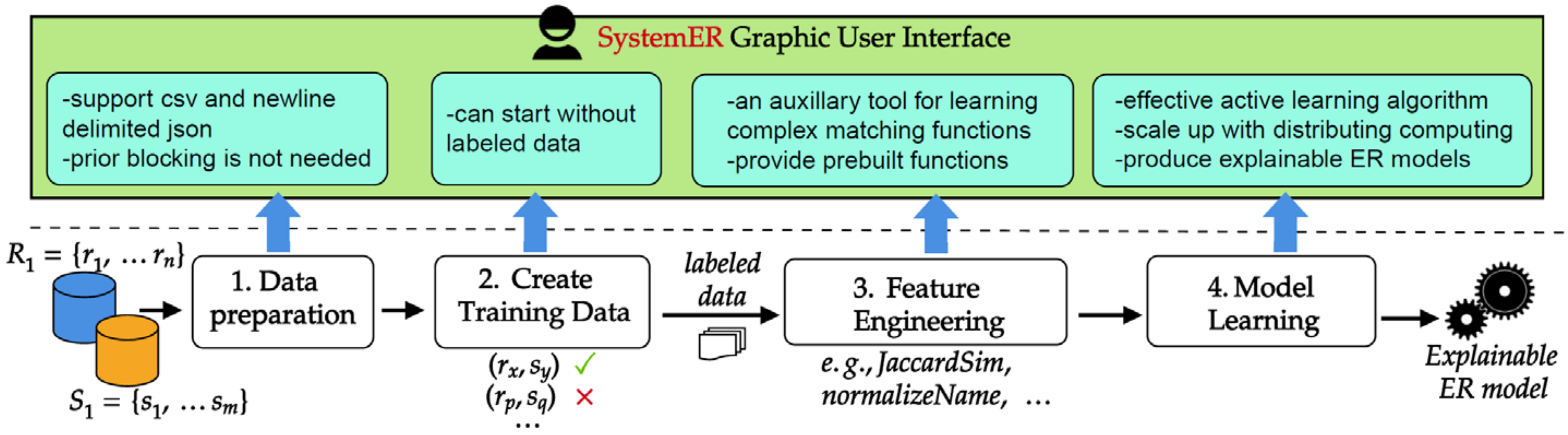
Facilities for Lay Users
GUIs, wizards, …
Power Users
EM Scenarios
How-to Guides
Development Stage
Supporting tools (as Python commands)
Data samples
EM Workflow
Production Stage
Supporting tools (as Python commands)
Original data
Python Interactive Environment Script Language
Data Analysis Stack
pandas, scikit-learn, matplotlib, …
Big Data Stack
PySpark, mrjob, Pydoop, …



[Yash Govind et al: Entity Matching Meets Data Science: A Progress Report from the Magellan Project. **SIGMOD 2019**]

SystemER (IBM Almaden – Research)

[Kun Qian, Lucian Popa, Prithviraj Sen: SystemER: A Human-in-the-loop System for Explainable Entity Resolution. **PVLDB 2019**]


SystemER Graphic User Interface
-support csv and newline delimited json
-prior blocking is not needed
-can start without labeled data
-an auxillary tool for learning complex matching functions
-provide prebuilt functions
-effective active learning algorithm
-scale up with distributing computing
-produce explainable ER models
$R_1 = \{r_1, \dots r_n\}$
$S_1 = \{s_1, \dots s_m\}$
1. Data preparation
2. Create Training Data
(r_x, s_y) ✓
(r_p, s_q) ✗
...
labeled data
3. Feature Engineering
e.g., JaccardSim, normalizeName, ...
4. Model Learning
Explainable ER model

Learns explainable ER rules (in HIL)

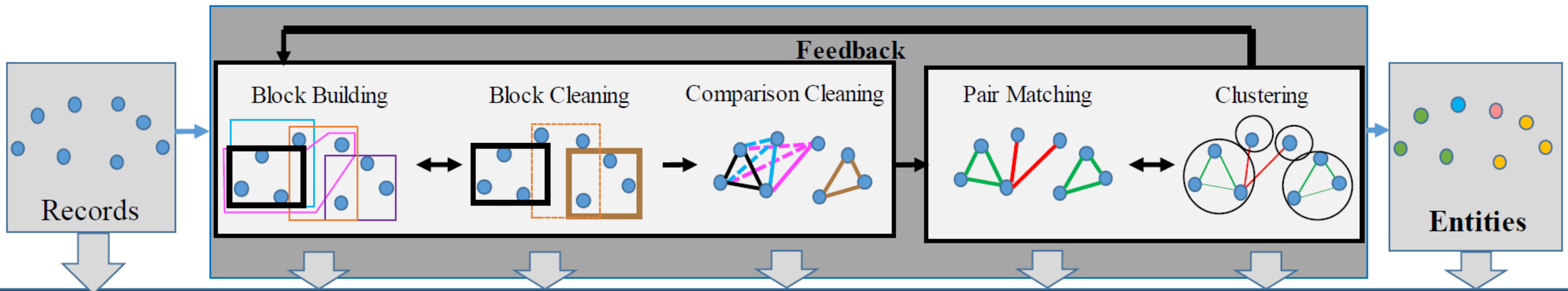
```
DBLP.title = ACM.title
AND DBLP.year = ACM.year
AND jaccardSim(DBLP.authors,ACM.authors)>0.1
AND jaccardSim(DBLP.venue,ACM.venue)>0.1
→ SamePaper(DBLP.id,ACM.id)
```

[Mauricio A. Hernández, Georgia Koutrika, Rajasekar Krishnamurthy, Lucian Popa, Ryan Wisnesky: HIL: a high-level scripting language for entity integration. **EDBT 2013**]

BEER (Blocking for Effective Entity Resolution)

[Sainyam Galhotra, Donatella Firmani, Barna Saha, and Divesh Srivastava: BEER: Blocking for Effective Entity Resolution, **SIGMOD 2021**]

Feedback after **1% sample**



- Supports csv files
- Allows SQL queries on the dataset

-Explore block hierarchy and its creation criterion
- Shows changes due to feedback

- Ranking of blocks based on quality
- Highlights progressive changes due to feedback

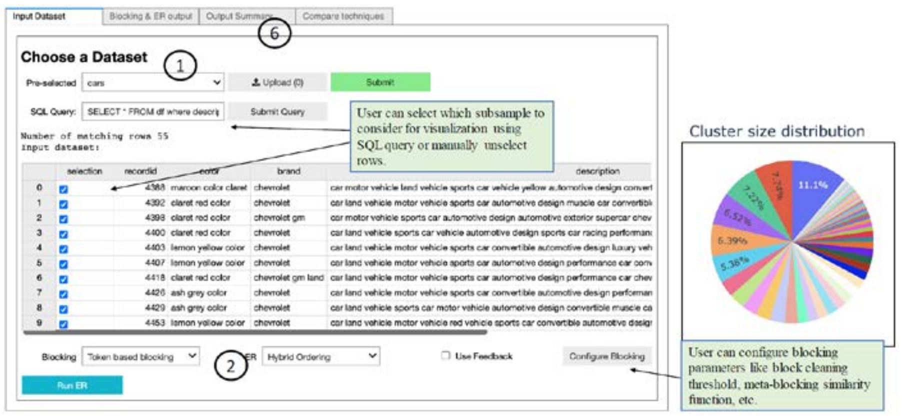
- Visualizes Meta-blocking graph [6]

-Visualizes matched and unmatched record pairs
- Allows custom matching functions

- Uses [3] for error correction
- Shows different clusters of entities
- Allows to change feedback

- Summary of entities
- Progressive behavior of the pipeline, running time and pipeline statistics

BEER GUI



Choose a Dataset

Pre-selected: cars

SQL Query: SELECT * FROM df where descri

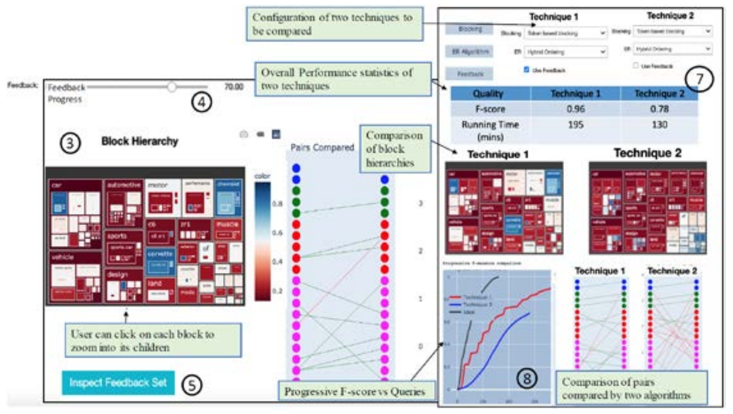
```
Number of matching rows 55
Input dataset:
```

User can select which subsample to consider for visualization using SQL query or manually unselect rows.

	selection	recordid	color	brand	description
0	✓	4388	maroon color claret	chevrolet	car motor vehicle land vehicle sports car vehicle yellow automotive design convert
1	✓	4392	claret red color	chevrolet	car land vehicle motor vehicle sports car automotive design muscle car convertibl
2	✓	4398	claret red color	chevrolet gm	car motor vehicle sports car automotive design automotive exterior supercar chev
3	✓	4400	claret red color	chevrolet	car land vehicle sports car vehicle automotive design sports car racing performan
4	✓	4403	lemon yellow color	chevrolet	car land vehicle motor vehicle sports car convertible automotive design luxury veh
5	✓	4407	lemon yellow color	chevrolet	car land vehicle motor vehicle sports car automotive design performance car conv
6	✓	4418	claret red color	chevrolet gm land	car land vehicle motor vehicle sports car automotive design performance car chev
7	✓	4426	ash grey color	chevrolet	car land vehicle motor vehicle sports car convertible automotive design performan
8	✓	4429	ash grey color	chevrolet	car land vehicle sports car motor vehicle automotive design convertible muscle ca
9	✓	4453	lemon yellow color	chevrolet	car land vehicle motor vehicle red vehicle sports car convertible automotive desig

Blocking: Token based blocking ER: Hybrid Ordering ☐ Use Feedback

User can configure blocking parameters like block cleaning threshold, meta-blocking similarity function, etc.



Configuration of two techniques to be compared

Technique 1: Blocking: Token based blocking; ER: Hybrid Ordering; ☑ Use Feedback

Technique 2: Blocking: Token based blocking; ER: Hybrid Ordering; ☐ Use Feedback

Overall Performance statistics of two techniques

Quality	Technique 1	Technique 2
F-score	0.96	0.78
Running Time (mins)	195	130

Comparison of block hierarchies

User can click on each block to zoom into its children

Progressive F-score vs Queries

Comparison of pairs compared by two algorithms

Example Applications

Previous DIA Exercise WS20/21

- **Task: Distributed Entity Resolution on Apache Spark**
  - 1-3 person teams, data: Uni Leipzig Benchmarks
  - Implement end-to-end **entity resolution** pipeline with Apache Spark for **data-parallel computation**

https://dbs.uni-leipzig.de/research/projects/object_matching/benchmark_datasets_for_entity_resolution

- **Example 1: DBLP, ACM, Google Scholar Publications**
  - `(title, authors, venue, year)`
  - Basic preprocessing via title capitalization, etc
  - How about leveraging the linked PDF papers?

In practice:
multi-modal data, and
feature engineering

- **Example 2: Amazon, Google Products**
  - `(name, description, manufacturer, price)`
  - NLP for matching medium and long descriptions, e.g., word embeddings
  - How about leveraging the product images (different angles)

Data Management – Autograding

- **Background**
  - **WS20/21:** automatic grading system for Data Management exercises
  - **Overview:** export submissions, run ingestion programs, execute queries, compare results and test queries, auto comments/grades, upload
  - **Problem:** Increasing automation requires better plagiarism detection
- **Plagiarism Detection via Entity Resolution**
  - https://issues.apache.org/jira/browse/SYSTEMDS-3191 (DIA WS21/22)
  - **Data preparation:** file names/properties, runtime, correctness
  - **Blocking:** by programming language, results sets
  - **Matching**
    - Exact matches via basic diff + threshold
    - Code similarity via SotA embeddings
  - **Clustering**
    - Connected components within each block (min sim threshold)

[Fangke Ye et al: MISIM: An End-to-End Neural Code Similarity System. **CoRR 2020** arxiv.org/pdf/2006.05265.pdf]

Summary and Q&A

- **Motivation and Terminology**
- **Entity Resolution Concepts**
- **Entity Resolution Tools**
- **Example Applications**

Fundamental Data Integration Technique, w/ lots of applications + remaining challenges

- **Next Lectures (Data Integration Architectures)**
  - 06 Data Cleaning and Data Fusion [Nov 12]
  - 07 Data Provenance and Blockchain [Nov 19]